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Artificial Intelligence Based - Oryza Sativa Leaf Ailment Recognition using DCT with Deep NN

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Abstract: India is one of the world's second-largest producers of Oryza Sativa (Rice). Oryza Sativa feeding almost half of the world population. Human consumption accounts for 85% of total production for Oryza Sativa. Since we have enough reason to give importance to the Oryza Sativa which is getting cultivated in the field, we must combine the technical field and the agriculture field together to prevent the plant disease in the early stage. In this paper, we propose an architecture that is associated with the classificatory model for analyzing and predicting the leaf disease in Oryza Sativa by using CNN where the network accepts an image of 227 x 227 pixels and Padding is included to keep the size of the feature maps from shrinking. Along with CNN, we have combined Fast Discrete Cosine Transform which gives us a better prediction of rice disease through signal processing tool for compressing images and sounds, found in standards of JPEG format and transforming the image from spatial domain to frequency domain.

Keywords*: Oryza Stiva, Ailment, Convolutional NN, DCT, Pre- Processing*

1. Introduction

The use of AI, ML and DL to food systems has been dubbed a "digital agricultural revolution" in recent years, with the promise to improve food security and reduce agriculture's environmental imprint. Rice (Oryza Sativa) is a major food crop in developing countries and the staple diet of more than half of the world's population. Various forms of fungus, bacteria, disease, pests, and other organisms attack Oryza Sativa. We've gathered digital photos of ailed fronds and are now processing them. Digital picture processing permits for a vast extent of algorithms to be implemented to the input facts, as well as the avoidance of problems like noise and distortion. Digital agriculture is the application of new and sophisticated technologies, integrated into a single system, to aid farmers and other players in the agricultural value chain in increasing food production. The combined data is then evaluated and interpreted, allowing the farmer to make more educated decisions. We presented the Fast-Discrete Cosine Transform algorithm as a pre-processing approach, followed by the Convolutional NN algorithm for evaluating and predicting illness in plant leaves.

The following is an outflow of the paper where Sec. 2 illustrates the literature survey on disease detection of Oryza Sativa leaf. Sec.3 describes the architecture of the DCT pre-processing technique and CNN models, as well as the datasets used in the trials, as well as their class and labels. The models' conclusions and performance are shown in Sec.4 where based on their capability to predict the accurate class among a variety of possibilities. Sec.5 discusses the study's limitations as well as possible future avenues for the system's development and enhancement. Section 6 brings the analysis to an end.

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2. Related Works

Controlling loss and boosting output requires the usage of correct procedures to recognize healthy and infected leaves. This segment discusses numerous algorithms for detecting ailment in plant.

Image Based Analysis:

Images may be analyzed and information retrieved for machine interpretation. The density - contrast of pixels in the picture can be regulate to the desired level. Images can be easily saved and retrieved, but image processing can be challenging. These involves different challenges like dealing with image unpredictability that cannot be eliminated, as well as handling noisy, incomplete, not totally dependable, imprecise, fragmented, confusing, inadequate, contradicting, and overloaded information.

Mutalib and team has [1] deployed the image processing method along with Artificial Intelligence for locating the weed species and recognizing the early stages of leaf diseases by fuzzy logic where the systems rely on erroneous data and inputs which can lead the accuracy on risk.

There could be a versatile strategy for applying Fuzzy Logic to address the issue which could emerge causing confusion. Study of [4] implemented the image processing approach for rice blast disease detection. Morphological operation is introduced for pre-processing and CNN as a classifier which give the accuracy rate of 97.43%. However, only one disease is focused for detection of disease. Different types of strategies introduced by [7] including "Histogram of Oriented Gradients (HOG)" and the feature classification is assisted by SVM which gives the resultant as 94.6%. Local Binary Patterns (LBP)" is used for separating various features which generates fairly extensive histograms and slow down identification speed, especially when dealing with huge face databases. Chawathe and team[12] presents an overview of image processing algorithm for likely disease-induced lesions in leaves and implemented Kawa Scheme language which runs on OpenJDK Java Virtual Machine (JVM). For image classification OneR & ZeroR is included to serve as baseline where ZeroR requires a larger initial investment.

Discrete Cosine Transform Based Analysis:

The input values from initialized 8 × 8 structure are normally figure-valued, whereas the output values are often actual-merit. As a result, we'll require a quantization phase to make some judgments regarding the merit in every Discrete Cosine Transform block and provide integer-valued output.

Haweel, R. T. and team [15] introduces the discrete cosine transform for image and signum function for good power compaction capabilities where both one-sided limits exist and are equal, a function's limit at x=a exists.. Study of [16] combines the two approaches wavelet transform and fast Fourier transform based on face based approach where the limited range of waveform data is processed and to compensate the spectral breakage, a window weighting function can be added to the waveform. Zhang, L. and collages [17] implemented Discrete Fractional Cosine Transform & Chaos for effective image encryption. The techniques used to compute the parameters are determined by the underlying dynamics of the data as well as the type of analysis being performed, which is typically complicated and not precise.

Deep Learning Based Analysis:-

To perform better than other policies, it needs a high extent of facts. Because of the complex data figures, training is exceedingly over-priced. DL also entail the use of over- priced GPUs and 100's of workspace. The user's price will arise as an outcome of this.

CNN algorithm is performed by [19] to differentiate and classify the diseased and healthy leaf with several layers of CNN where the training process can take a long time if the machine is not supported by the powerful GPU. Adedoja, A. and team [20] implemented the NASNet architecture for recognition of plant disease using leaf images. The entire process of creating neural networks will entail an analysis, which is time-consuming and costly. Study of [21] approached 6 type of data augmentation method for identification of plant disease which archives the accuracy of 96.46% along with K-NN for simple memory-based classification. During the training phase the data isn't used to construct any discriminative functions. Sladojevic and team [23] deployed CNN along with a deep learning framework namely Caffee for classification of leaf image which requires, C++ / Cuda code for every new layers which is exposed to different architectures.

To overcome the challenges in pre-processing, duration of training process, cost, identification speed, precise data and better accuracy we proposed the discrete cosine transform with CNN algorithm for better accuracy value of 98.96%

3. Materials and Methods

3.1. *Convolutional N Networks*

A Convolutional NN also known as Feed-Forward NN which processes input in a grid like structure to evaluate visual pictures. Many hidden layers in a CNN supports in the extraction of data from a picture. Convolution layer: Obtaining useful information from the images begins her. A convolution layer consists of many filters that perform the convolution action. Every image is seen as a pixel merit matrix.

Here is a 5x5 image with pixel values of 0 or 1. In a filter matrix which consist a 3x3 dimension is also involve. To obtain the convolved attribute matrix, glide filter matrix above image and evaluate the dot product.

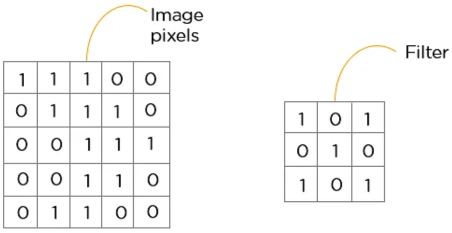


Fig.1. Convolutional Layer

Rectified Linear Unit: The feature maps must be transferred to the ReLU layer after they have been eliminated. In ReLU, all negative pixels are converted to zero, causing the network to become nonlinear and producing a rectified feature map. The following is a graph of a ReLU function:

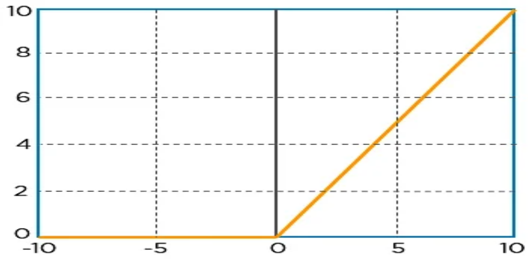
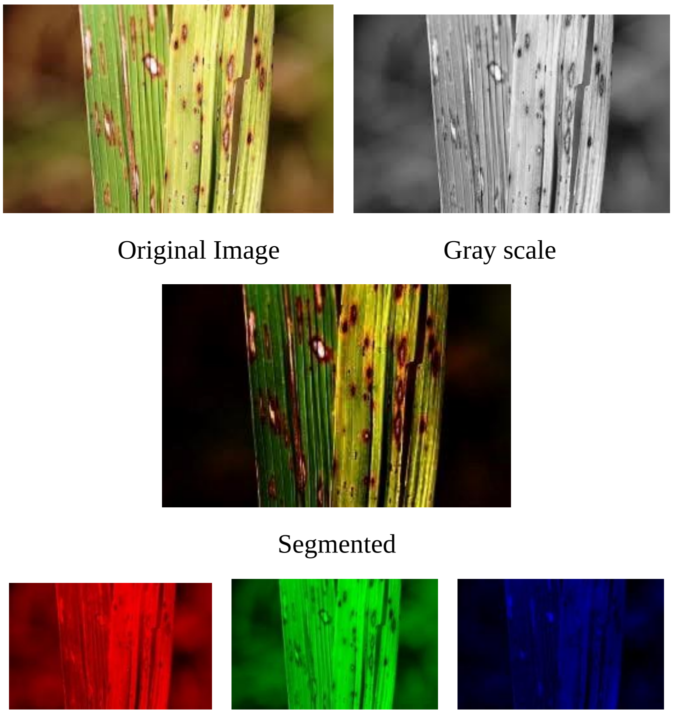


Fig. 2. Relu Layer

R(z) = max(0.z) = max is the formula used in Relu. A Down Sampling technique - Pooling is used for reducing the dimensionality of a feature map. Rectified feature is sent via a pooling layer to form the pooled feature map.

3.2. *AlexNet*

Computer vision has a lot of uses for AlexNet, which is a governing architecture for a little object-sensing work. AlexNet is a convolutional neural network with eight layers. Million and above images can be imported from ImageNet database through a pre-trained version of the network. AlexNet's success can be attributed in part to its ability to train with GPUs and to train a large number of parameters.



Original Image Gray scale

Segmented

Red Green Blue

Fig: 3 Original – Gray scale – Segmented – RGB Image

3.3. *DCT*

A Discrete Cosine Transform depicts a limited series of facts points as a volume of cosine functions quiver at unlike frequencies. The DCT is a method for determine redundancy by modifying picture pixels in the structural domain towards the frequency domain.

These values provide all of the information required to define the eight pixels. Simply said, the purpose of the DCT transformation phase is to discover "information in the picture signal that can be successfully 'thrown away' without significantly diminishing the image's quality."

SLNO	MODEL	NO. OF LAYER	PARAMETERS	SIZE
1	AlexNet	8	61 million	-
2	LeNet	5	3264	-
3	Manual Net	7	15	-
4	VGGNet-16	23	138	528 MB
5	VGGNet-19	26	143	549 MB
6	Inception-V1	27	7	-
7	Inception-V3	42	27	93 MB
8	ResNet-152	152	50	132 MB
9	ResNet-101	101	44	171 MB
10	Inception ResNetV2	572	55	215 MB
11	MobileNet-V1	28	4.2	16 MB
12	MobileNet-V2	28	3.37	14 MB

Table 1: Comparison of layer number & parameter size with several CNN designs

The merits of layers and parameter sizes of variegated CNN architectures are shown in Table 1. AlexNet has an 8-layer structure with 60 million parameters, while VGGNet-16 and Google Net have 138 & 7 million parameters. ResNet152 has 152 layers with a parameter size of 50 million. The parameter sizes for InceptionV3, MobileNetV1, and MobileNetV2 are 27, 4.2, and 3.37 million, correspondingly. We employed the InceptionV3, MobileNetV2, Inception ResNetV2, & EfficientNetB0 architectures to identify various rice leaf illnesses utilizing the leaves of diseased plants in our research. These models were chosen because their parameter sizes are less than those of other designs. We used a pre-trained weight from the ILSVRC dataset during implementation

3.4. *Data Sets*

For training & testing, we utilized the Plant Village and Kaggle dataset, which comprises 6100 units of diseased and healthy rice leaves.

The fact lists the unit of classes and pictures in per capita class, in addition to their usual and research based label and disease-effect viruses.

All of the leaf shots were used to build a training 80% & testing 20%.

CLASS	*DISEASE NAME*	*GENESIS VIRUS NAME*	*GENUS OF DISEASE*	*NO. OF IMAGES*
CL1	Brown Spot	Cochliobolus miyabeanus	Fungus	2,300
CL2	Hispa	Dicladispa armigera	Invasive Pest	1,700
CL3	Leaf Blash	Magnaporthe grisea	Fungus	1.900
CL4	Healthy	-	-	2,000

Table 2. Detailed description of dataset with relative information.

Brown Spot *Hispa*

Leaf Blash *Healthy*

Fig 4: Sample Images of the diseased and healthy leaf

4. Proposed Methodology

4.1. *Working of Discrete Cosine Transform*

The DCT splits pictures towards portions with differentiating frequencies. The rare notable frequencies are removed during a preceding called quantization, in which few of the compression really takes place. In the decomposition process, only the most relevant frequencies are employed to extract the picture.

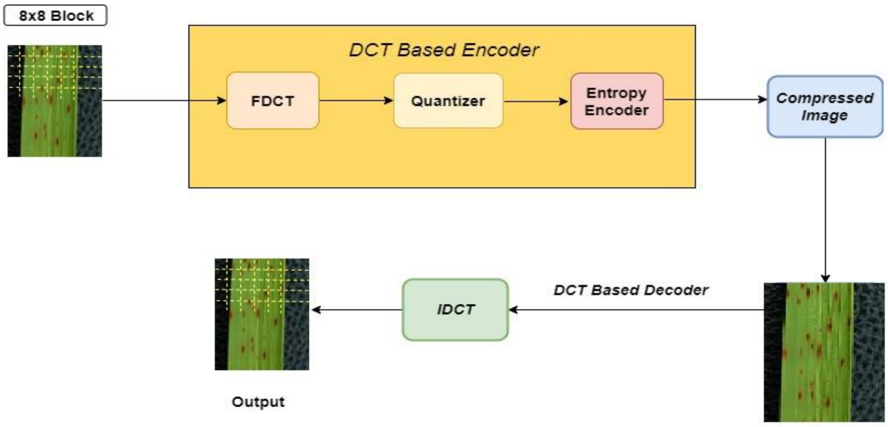


Fig 5: DCT Architecture

The steps are listed below.

1. The picture is divided up into 8x8 pixel blocks.

2. The DCT is implemented to each and every blocks from all the four sides.(Left, Right, Top and Down)

3. By using quantization, each block is compressed.

4. The compressed block array of the image takes up a fraction of the space it would otherwise.

5. During decompression, the desired image is rebuilt using the Inverse Discrete Cosine Transform (IDCT)

4.2. *Working of Alex net*

AlexNet is designed of 3 convolutional layers and 5 fully linked layers. Several Convolutional Kernels extract significant properties from a photograph. Through an Overlapping Max Pooling layer, the output of the 5th convolutional layer is fed into a sequence of two fully connected layers

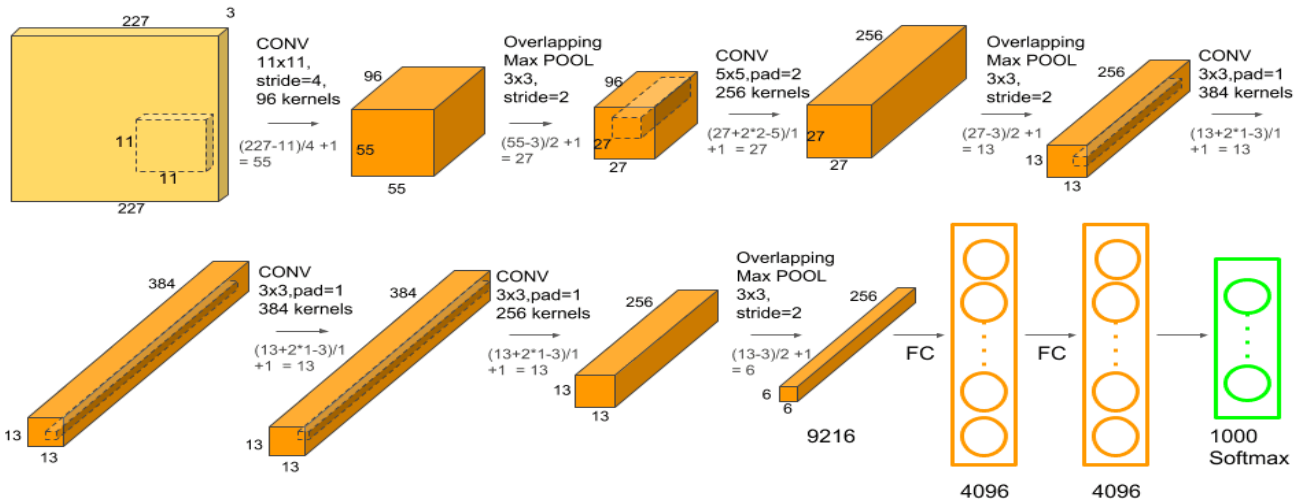


Fig 6: Alex net Architecture (Source: https://learnopencv.com/wp-content/uploads/2018/05/AlexNet-1.png)

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	227x227x3	-	-	-
1	Convolution	96	55x55x96	11x11	4	Relu
	Max Pooling	96	27x27x96	3x3	2	Relu
2	Convolution	256	27x27x96	5x5	1	Relu
	Max Pooling	256	13x13x256	3x3	2	Relu
3	Convolution	384	13x13x384	3x3	1	Relu
4	Convolution	384	13x13x384	3x3	1	Relu
5	Convolution	256	13x13x256	3x3	1	Relu
	Max Pooling	256	6x6x256	3x3	2	Relu
6	FC	-	4096	-	-	Relu
7	FC	-	4096	-	-	Relu
Output	FC	-	1000	-	-	Softmax

Table 3: Alex Net Parameters Description

Table3 describes the parameters of Alex Net where the 1st convolution layer is applied, with the feature map of 96 filters with 11 x 11 size along with 4 stride. This layer uses relu activation function. The final feature map is 55 x 55 x 96 pixels. In output feature map, the number of filters becomes a channel. Following this is the first Max pooling layer with 3 x 3 kernel size and has a stride of 2. The output is a 27 x 27 x 96 feature map. The second convolution process follows. There are 256 feature maps, and the filter size has been lowered to 5 x 5. The stride is 1 and 2. The activation function is relu. The result now measures 27 x 27 x 256 pixels. We used a 3 x 3 kernel sized max-pooling layer along with stride 2 again. The generated feature map is of size 13 x 13 x 256. With the filter size of 384 with the size 3 x 3 stride 1 along with padding 1. The 3rd convolution operation is activated and the activation function is relu. The structure of the produced feature map is 13 x 13 x 384.The 4th convolution process uses 384 filters with a dimension size of 3 x 3. A stride of 1 is achieved with cushioning. In addition, the rectified linear activation function is the output size of 13 x 13 x 384, same as previous. Following that, we get the final 3X3 convolution layer with filter size of 256. The stride and padding have been set to 1, and the activation feature has been disabled. The generated feature map is 13 x 13 x 256 in size. So far, the number of filters has increased. As we progress through the architecture, additional features are extracted. In addition, the filter size is shrinking, which indicates that the starting filter was larger and is shrinking as we progress, resulting in a smaller feature map. Afterward, we apply the third max-pooling layer of size 3 x 3 and stride 2. As a result, The feature map of the shape 6 x 6 x 256 is created. The 1st FC layer with a relu activation mechanism comes. The output is 4096 bytes in size. Then a 2nd FC layer with 4096 neurons and the activation of RELU function will follow. As there are 10000 classes in the data set, we have the final fully connected layer or output layer with 1000 neurons. Softmax as the activation function used at this layer. Here is the architecture of the Alex net model which features an entire parameters of 62.3M.

4.3. *Fast Discrete Cosine Transform and Convolutional NN Implementation*

As an input, we used a infected photo of a leaf, deleting each patch from each pixel value, which was then sorted by energy, with those with a high degree of energy being kept by thresholding. Finally, the pictures were transformed to 8x8 pixels, and the input image was divided into 8-by-8 blocks, with each block receiving a two-dimensional DCT as a pre-processing and classification approach. The DCT coefficients are quantized, coded, and transferred after that. The JPEG receiver (or JPEG file reader) decodes the quantized DCT coefficients, then calculates the inverse two-dimensional DCT for each block and reassembles the blocks into a single image. CNN uses the image from the DCT block to assign significance (learnable weights and biases) to the image's various properties and objects, allowing it to differentiate between them. Convolutional layers then conduct a convolution operation to the input before passing the output to the next layer. Convolution is a technique for combining the values of all the pixels in a receptive region into a single value. The Pooling layers are then applied to the feature maps to minimize their size. As a result, both the quantity of processing and the number of parameters to learn in the network are reduced. Flattening process of conversion of data into a 1D array for utilizing in the succeeding layer. The softmax activation function normalizes neural network output to fit between zero and one, while the fully connected (FC) neural network classifies input into several classifications.

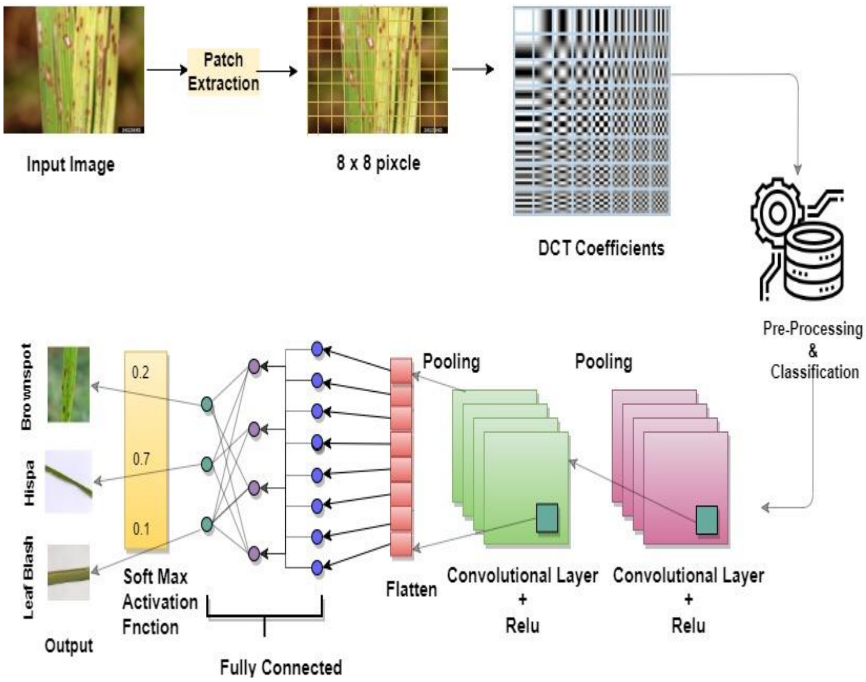


Fig 7: Fast DCT & Alex net Architecture

5. Result

The parameters listed in Table 5 were used in the CNN designs that were implemented, as described in the previous section. Fast DCT + Alex Net has highest accuracy when compared to InceptionV3, MobileNetV2, & InceptionResNetV2. Performance was evaluated using a range of metrics, including accuracy, F1 score, precision, recall, training loss, and time required per epoch.

The following are the performance metrics that we examine in our suggested work.

- Performance accuracy is defined as the ratio of the total number of properly identified photographs to the total number of images.
- The loss function of the design reveals how well it represents the data.
- The fraction of precisely anticipated observations TP to total positive predictions TP + FP is known as precision.
- The percentage of correctly predicted observations TP to the total number of observations in a class TP+FN is referred to □ as recall.
- The F1 score is the harmonic mean of accuracy and recall.
- Time required to train each DL model per epoch (in seconds).

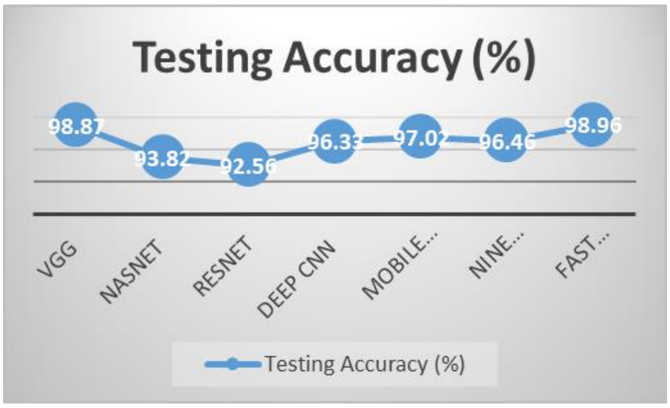
Parameters	Values
Training Epoch	*50*
Batch size	*30 – 160*
Learning Rate	*0.01*

Table 4. Parameters used in CNN for training.

Architecture Model	*Testing Acc (%)*	*Loss*	*Epoch*	*Avg Time (s/Epoch)*
VGG	98.87	0.0542	49	4208
NASNet	93.82	-	9	-
ResNet	92.56	-	-	-
Deep CNN	96.33	-	100,000	-
MobileNet V2	97.02	0.092150	50	565
Nine Layer CNN	96.46	0.2487	3000	-
Fast DCT + Alex Net	**98.96**	**0.0129**	**50**	**545**

Table 5. Comparison of Architecture

Figure 8 specify that the carry out methodology achieved finer execution in terms of the of accuracy And shown execution accuracy with esteem to the unlike values utilized in the network.



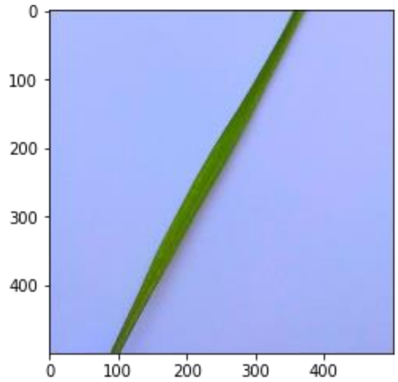
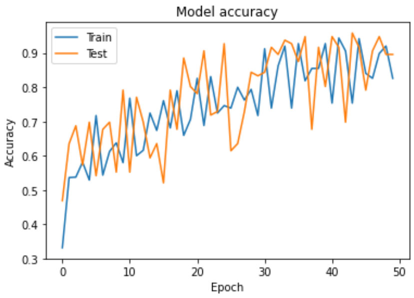
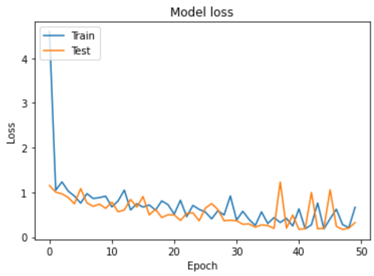


Fig. 8. Testing Accuracy Graph **Fig 9:** An example of rice leaf categorization from test image set

The clarity of map is set on by the severity and accuracy with which the attribute are drawn, as shown in Figure 10. Framing accuracy differs from 0. 1 mm to 0.4 mm, with a mean merit of 0.25 mm being the most generally used plotting precision. It's the entire integer of errors made in each training or validation set for each example in Figure 11.





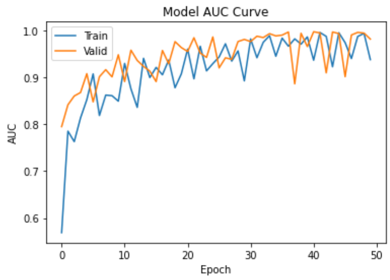


Fig. 10. Accuracy Graph **Fig. 11.** Loss Graph **Fig 12:** AUC Graph

In the accompanying pictures Fig 11, two graphs represent the losses of two different models; the left graph has a large loss, while the right graph has a little loss.

Figure 12: AUC measures the likelihood that a random positive example will be positioned above a random negative (red). The AUC ranges between 0 and 1. The AUC of a model with 100 percent wrong predictions is 0.0, whereas the AUC of a model with 100 percent accurate predictions is 1.0.

6. Discussion

Based on the performance comparison of various architectures Fast DCT + Alex Net gives us the highest accuracy of 98.96% with the loss percentage of 0.0129 in the epoch 50 with an average time of 545 s/epoch whereas in VGG architecture [19] the highest accuracy reaches to 98.87% with the loss percentage of 0.0542 in 49th epoch and takes more testing time of 4208 s/epoch. NASNet [20] and ResNet architecture gives 93.82% & 92.56% of accuracy with unspecified loss percentage and average time. Mobile Net V2 gives the accuracy of 97.02 % in 50 epochs and 565 s/epoch. Deep CNN [23] and Nine Layer CNN [21] architecture show almost the same accuracy of 96.33% and 96.46% with the enormous training epoch of 100,000 & 3000 which would have led to an extreme number of duration for training in seconds per epoch. Therefore, Fast DCT + Alex Net architecture provides pre-processing method through DCT and passes the output to the next layer i.e. Alex Net which classify the image through various layers and conclude with the prediction of the affected disease.

7. Conclusion

Many new approaches for detecting and classifying plant diseases utilizing infected leaves of plants have been created. There is still no reliable and cost-effective commercial method for diagnosing illnesses. For the diagnosis of Rice leaf illnesses utilizing healthy and infected leaf photos of plants, we employed Discrete Cosine Transform as a pre-processing technique and Deep Learning models Convolutional Neural Network's deep architecture Alex-Net. We utilized the standard Plant Village dataset with 6,100 photos, all recorded under lab settings, to train and test the model. This series of photos includes four different types of healthy and infected rice leaves. We achieved the finest accuracy rate of 98.96 % in the DCT + Alex Net model after partitioning the dataset in ratio of (Training) 80: 20 (Testing).

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